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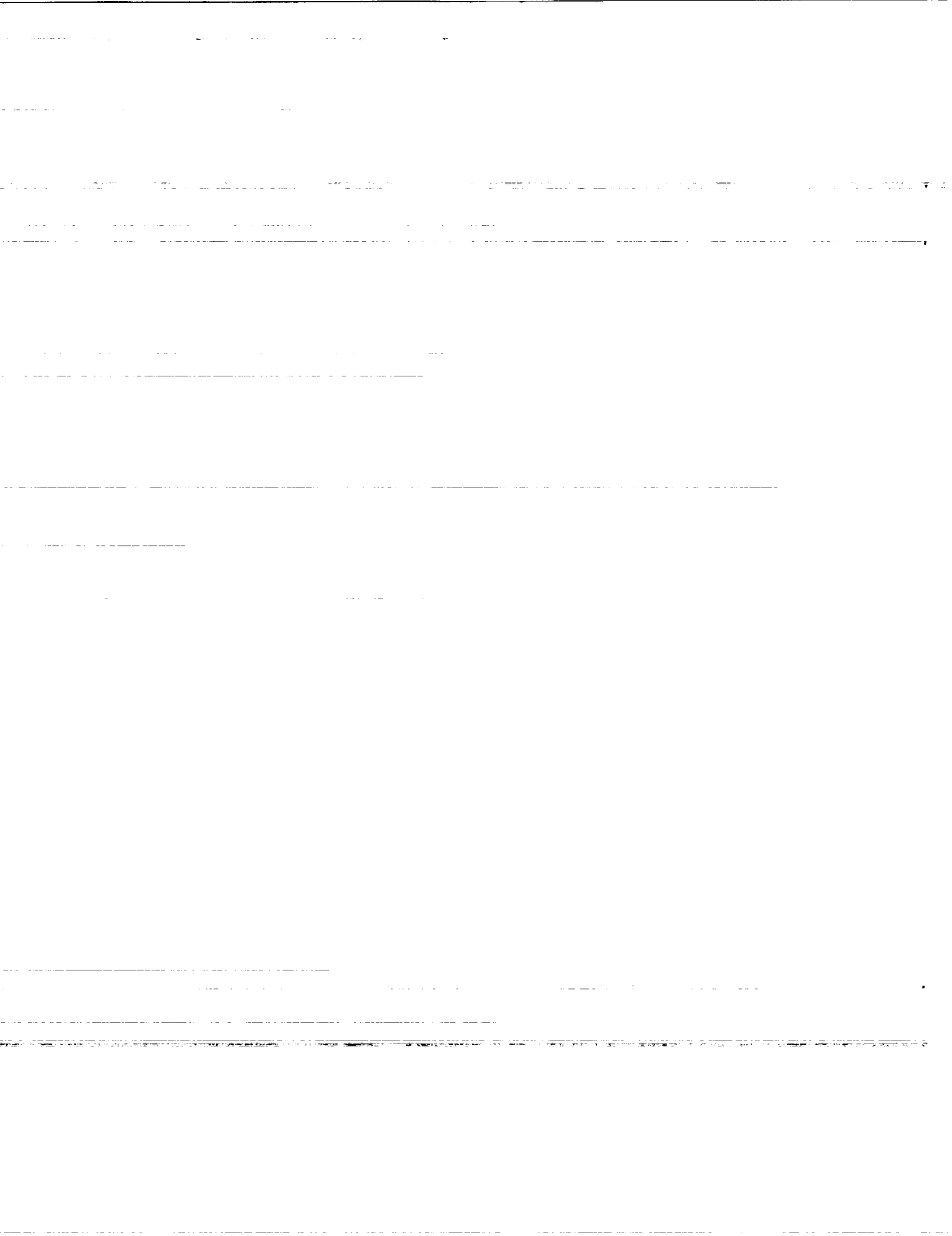


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ON-LINE IMPLEMENTATION OF NONLINEAR PARAMETER ESTIMATION FOR THE SPACE SHUTTLE MAIN ENGINE

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Abstract

We investigate the performance of a nonlinear estimation scheme applied to the estimation of several parameters in a performance model of the Space Shuttle Main Engine. The nonlinear estimator is based upon the extended Kalman filter which has been augmented to provide estimates of several key performance variables. The estimated parameters are directly related to the efficiency of both the low pressure and high pressure fuel turbopumps. Decreases in the parameter estimates may be interpreted as degradations in turbine and/or pump efficiencies which can be useful measures for an on-line health monitoring algorithm. This paper extends previous work which has focused on off-line parameter estimation by investigating the filter's on-line potential from a computational standpoint. In addition, we examine the robustness of the algorithm to unmodelled dynamics. The filter uses a reduced-order model of the engine that includes only fuel-side dynamics. The on-line results produced during this study are comparable to off-line results generated previously. The results show that the parameter estimates are sensitive to dynamics not included in the filter model. Off-line results using an extended Kalman filter with a full order engine model to address the robustness problems of the reduced-order model are also presented.

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Introduction

The Space Shuttle Main Engine (SSME) is the first large scale reusable rocket engine developed from a long line of expendable rocket technology. High thrust requirements have pushed material limits and made durability an important issue. Much work has been directed toward developing off-line monitoring algorithms to determine the relative "health" of the propulsion system. An effective health monitoring scheme provides the capability to detect engine degradations before significant damage occurs. Corrective action may be taken by the engine controller using information from an on-line health monitoring algorithm such that damage can be minimized or avoided. When a monitoring algorithm is used as a post processor, indications of engine degradations can be used to determine if maintenance is required with focus on specific components to help reduce operational costs associated with the SSME fleet.

A nonlinear parameter estimator based on the extended Kalman filter¹ (EKF) has proven effective in a post-processing capacity. Recent work at the Space Engineering Center for System Health Management Technology at the University of Cincinnati has demonstrated that the EKF is a viable method for off-line parameter estimation for use in a health monitoring scheme for the SSME². The filter estimates parameters in a nonlinear engine model whose variation is indicative of fuel-side turbomachinery degradations such as frictional losses or bearing wear. Degradation of these parameters can be interpreted as a decrease in turbomachinery efficiency. The filter uses a reduced-order model representing only the fuel-side component dynamics and has been evaluated as an off-line algorithm using both simulated and hot fire data. The results show that the filter provides satisfactory estimates of the fuel-side turbomachinery efficiency parameters and tracks the true values well when degradations to the low pressure fuel turbopump (LPFT) efficiency are introduced. However, degradations to the high pressure fuel turbopump (HPFT) result in unsatisfactory estimates of both efficiency parameters, primarily due to the dynamics of the engine that are not included. Open loop degradations in the HPFT efficiency ultimately result in an increase in mixture ratio in the main combustion chamber. The resulting rise in combustion temperature increases the energy in the cooling circuit which will affect the LPFT and the rest of the system. A full-order filter including both fuel and LOX dynamics has been developed to address this problem. Preliminary results are presented here.

The present effort extends the work on parameter estimation in a post-processing capacity² and focuses on the on-line implementation of the EKF. The primary motivation for this study is the investigation of filter performance in the presence of a controller. Closed loop control tends to mask information needed by the filter to accurately estimate the parameters. However, satisfactory estimates were obtained for degradations to the LPFT. As a result of the poor open loop performance for HPFT degradations, they were not considered in the on-line analysis. Sensitivity to unmodelled dynamics for the reduced order filter was investigated by examining a degradation in

the high pressure oxidizer turbopump efficiency and an increase in the LPFT shaft seal leakage³. The LPFT shaft seal leakage is particularly interesting because it decreases the efficiency of the turbopump without explicitly changing the efficiency parameter in the model which is estimated by the EKF.

In this paper, we introduce the EKF algorithm, drawing attention to areas of interest for on-line implementation. The application of the EKF to the SSME is discussed, followed by a presentation of off-line results using the full-order filter. Modifications made to the filter algorithm to improve execution speed for on-line implementation are presented and their impact on filter performance is discussed. On-line results demonstrate the feasibility of this approach and draw further attention to the shortcomings of the reduced order filter.

EKF-based Parameter Estimation

The extended Kalman filter is a state estimator for nonlinear systems and can be modified to provide parameter estimates in a straightforward manner¹. A brief overview of the algorithm with a focus on the equations requiring modification for real-time implementation is given below.

The nonlinear system model of the SSME⁴ adapted for use with the EKF has continuous, nonlinear, time invariant state equations with linear discrete measurement equations written as

$$\begin{bmatrix} \dot{x}(t) \\ \dot{a}(t) \end{bmatrix} = \begin{bmatrix} f(x,a,u,t) \\ 0 \end{bmatrix} + \begin{bmatrix} \omega(t) \\ q(t) \end{bmatrix}, \quad (1)$$

$$y_n = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x_n \\ a_n \end{bmatrix} + v_n; \quad C = \begin{bmatrix} I & 0 \end{bmatrix},$$

where $u \in \mathbb{R}^m$ represents the propellant valve angles, $x \in \mathbb{R}^p$ represents the engine state, $y_n \in \mathbb{R}^b$ represents the measurements used by the filter, and $a \in \mathbb{R}^r$ represents the parameters we are interested in estimating. The system and measurement noise, $\omega(t)$ and v_n respectively, are white and $q(t)$ is a pseudo noise which is assumed to drive the parameter values for the purpose of avoiding slow convergence of the parameter estimates, when no noise process typically drives the actual parameter values. For simplicity, we assume the measurements are states. The relationship between states and measurements is generally nonlinear for the SSME. However, several states are measured directly allowing use of eq (1) without additional computational burden. These equations may be rewritten in more conventional notation as

$$\begin{aligned} \dot{z}(t) &= f_a(z,u,t) + \omega_a(t), \\ y_n &= C_z z_n + v_n. \end{aligned} \quad (2)$$

A flow chart of the EKF algorithm is given in Figure 1. Propagation of the state estimates between measurements at t_n and t_{n+1} is carried out by integrating the nonlinear state equations in eq. (2). Fast dynamics in typical nonlinear models often prohibit the integration interval ($\delta t = t_{k+1} -$

t_k) from being the full measurement cycle ($\Delta t = t_{n+1} - t_n$). Hence, integration is performed over N consecutive subintervals such that $\Delta t = N \delta t$ giving

$$\hat{z}(k+1/k) = \hat{z}(k/k) + \int_{t_k}^{t_{k+1}} f_a(\hat{z}(\tau/k), u(t_k), \tau) d\tau. \quad (3)$$

Similarly, propagation of the error covariance matrix (P) is performed for each of the N subintervals using

$$P(k+1/k) = \Phi(k+1/k)P(k/k)\Phi^T(k+1/k) + Q_k \quad (4)$$

where Q_k represents the discrete covariance matrix of the system noise in eq. (1) using interval length δt . The discrete transition matrix (Φ) can be constructed by computing the Jacobian of the state equations at each t_{k+1} and discretizing to give

$$\Phi(k+1/k) = e^{G(t_{k+1}-t_k)} \quad (5)$$

where the elements of G are

$$g_{ij} = \left. \frac{df_a^i}{dz_j} \right|_{\hat{z}(k+1/k), u, t_{k+1}} \quad i, j = 1, \dots, p.$$

Execution of the integration, linearization and discretization of states in the EKF algorithm is very time consuming. This poses no significant difficulty for off-line application of the algorithm. However, an on-line implementation cannot accommodate the large amounts of execution time required to perform eqs. (3-5). As a result, several modifications can be made to simplify the algorithm thereby improving execution time for on-line use. As shown in figure 1, once the measurement data is received, the remainder of the EKF algorithm proceeds exactly as a standard Kalman filter.

Application of the EKF to the SSME

A 41 state nonlinear, real-time model of the SSME has been developed by Rocketdyne⁴ for evaluation of hardware in the loop (e.g. Block I controller). The dynamic model is parameterized by "B values" which can be tuned to reflect a nominal engine balance with representative dynamic performance. In this work, we focus on those B values which can be interpreted as efficiencies in the torque equations of both the low pressure and high pressure fuel turbopump models. In particular, the equations for the LPFT and HPFT torque are given by

$$\tau_{ft1} = B16 * DW_{ft1} * \sqrt{\Delta h_{ft1}} * \Gamma_{ft1}(v/c_{ft1}) \quad (6)$$

and

$$\tau_{ft2} = B26 * DW_{ft2} * \sqrt{\Delta h_{ft2}} * \Gamma_{ft2}(v/c_{ft2}) \quad (7)$$

respectively, where DW represents mass flow, Δh represents the change in enthalpy across the turbine, and Γ represents the torque characteristics as a function of the ratio of turbine tip speed to flow velocity. The parameters $B16$ and $B26$ in eqs. 6 and 7 are directly related to a lumped turbine efficiency³. Care must be taken in interpreting the results of varying these parameters since the

real-time model is not valid for off nominal operation. However, they can provide much insight as a first order approximation.

A reduced order EKF based only on fuel-side dynamics (14 states) has been developed⁵ at the University of Cincinnati to estimate B16 and B26 at several SSME power levels in a typical SSME mission. Derivatives of the dynamic equations were computed analytically to allow computation of the discrete state transition matrix of eq. (5) as the state estimate evolves. The 16th order filter uses only three measurements, LPFT shaft speed, HPFT shaft speed and fuel preburner pressure all of which are states in the dynamic engine model giving rise to the measurement model in eq. (1). Several other measurements are available for use, however only these three were used for this study. They were selected as a convenient starting point for feasibility studies and are not necessarily the optimal set of measurements.

Off-line Results

The EKF described above has previously been evaluated as an off-line algorithm using both simulation⁵ and hot-fire data at rated power. Figures 2 through 5 show off-line simulation results at rated power for ramp decreases in the parameter to be estimated when no controller is present. Figures 2 and 3 show that the filter provides acceptable estimates of B16 and B26 for degradations of the LPFT efficiency parameter B16. The B26 estimate is affected by the B16 degradation initially, however it recovers quickly and converges to the correct value.

Figures 4 and 5 show that degradations of the HPFT efficiency parameter result in unsatisfactory estimates of both B16 and B26. The B26 estimate in Figure 4 predicts a decrease in efficiency at the time the anomaly occurred. Unfortunately, the estimate of B16 indicates a rise in LPFT efficiency has occurred. The increase in the efficiency estimate for the LPFT results from the increase in temperature in the main combustion chamber caused by the decrease in fuel entering the combustor. Due to the poor performance of the reduced order filter in estimating B26, transient results for the on-line implementation are not included in this work.

A full order filter has been developed to address the limitations of the reduced order model in estimating B26. Preliminary results shown in figures 6 and 7 indicate that the estimates can be improved by including LOX side dynamics. However, filter performance for both the full and reduced order models is extremely sensitive to the selection of the characteristics of the pseudonoise ($q(t)$) in eq. (1). Figure 6 shows the parameter estimate converging nicely to the degraded efficiency parameter value. The estimate is rather noisy, indicating that the filter requires additional tuning. Estimates of B16, when the HPFT efficiency parameter is degraded, using this filter are not yet available. Figure 7 shows the performance of the B16 estimate for the full order filter which should be compared with the reduced order filter results given in figure 2. The estimate

agrees favorably with earlier results giving us added confidence in the full order filter implementation.

On-line Implementation

The off-line results demonstrate the feasibility of the EKF parameter estimator as a post-processor to estimate fuel-side turbopump efficiencies. This information can be used to detect system degradations between firings and can be used as part of an engine maintenance procedure to indicate when turbomachinery requires work. However, on-line estimation of these efficiencies could provide timely information to a controller thereby changing the control of the engine to maintain performance while minimizing the burden on "healthy" components.

A first cut at on-line implementation of the reduced order filter was performed at NASA Lewis Research Center (LeRC). Two simulation environments were available for this study, a real-time simulation located on an ADI AD100 and a Matrix_x simulation⁶. The SSME models that describe the dynamics for the simulations are similar in both environments. However, the AD100 simulation has been modified to incorporate a number of different failure modes which has necessitated several changes to the computation of key performance variables³. Both simulations provide the capability to perform open loop evaluation for comparison with off-line results. The AD100 simulation allows filter evaluation in scaled time with the Block 1 controller, which is the current SSME controller. The Matrix_x simulation provides the opportunity to evaluate the filter using a multivariable controller⁷ to evaluate several different degradation scenarios and examine the sensitivity of the filter performance to the controller structure.

The original EKF implementation was not intended for on-line use, therefore several modifications were made to improve execution speed. Due to the lack of a reliable measure, only a gross approximation of the amount of reduction achieved by individual modifications is available. A 4th order, variable step, Runge-Kutta integration scheme was used in the filter to perform the integration of eq. (3). It is well known that this method requires considerable computation time, therefore it was replaced with the Burlisch-Stoer method⁸. This modification significantly reduced the time required to execute the algorithm, although some systems encounter robustness problems when using this integration method⁸. However, the method has performed well on the SSME model to date. This change had no apparent affect on the filter's convergence characteristics.

The linearization and discretization of eq. (5) are also large contributors to execution time in the EKF algorithm. The impact of these calculations on execution speed was reduced by performing them only once per measurement cycle (t_n) rather than once per integration cycle (t_k) and by replacing the matrix exponential in (5) with a Tustin approximation for discretization. These approximations noticeably reduced execution time with no noticeable effect on filter performance.

The number (N) of linearizations performed during each measurement cycle can be reduced due to the behavior of the SSME dynamics at constant power setting. Linearization may need to be performed more often to achieve acceptable results for transient conditions. Also, it is conceivable that performing a larger number of linearizations could possibly reduce execution time by reducing the time required to perform the variable step integration by improving the accuracy of the error covariance (P). Off-line results indicate that perhaps two linearizations per measurement cycle would result in faster execution time than one. However, due to the lack of a reliable metric, this issue was not pursued further.

Incorporation of these modifications along with several minor changes result in an improvement of execution time of almost 60% on an Intel 486 based special purpose computer. As a result, the on-line simulations were performed in scaled time at 250 times rather than 600 times real time as required by the original implementation. A significant improvement was made with relatively straightforward modifications to the algorithm. Improved computing power, in addition to more efficient programming methods should further reduce execution time.

On-Line Results

The primary consideration for on-line implementation is examination of the filter behavior in the presence of a controller. Closed loop control tends to mask information required for convergence of the parameter estimate to the correct value. Moreover, the filter performance can be sensitive to controller structure. Figures 8 through 11 compare open and closed loop simulation results using both the AD100 (Block I control) and Matrix_X (multivariable control). Open and closed loop results compare favorably. However, notice the bias from the actual value that exists for each case. This is due to the fact that the model used to tune the filter is different from the those used to provide the measurement data. This indicates that robustness to unmodelled dynamics may be an issue in this case as well as for the HPFT efficiency degradation. On-line implementation of the full-order filter could provide some insight into this issue and will be examined in the future. Although the estimates provided by the reduced order filter are not exact, they clearly indicate a degradation has occurred providing information that may be useful to a controller.

Another consideration for the EKF implementation for the SSME is the evaluation of degradations that should be interpreted as LPFT efficiency degradations but are not introduced by decreasing B16. Taking advantage of the seal leakage modelled in the AD100 simulation, the LPFT efficiency is reduced without decreasing B16 by increasing the LPFT shaft seal clearance by 250 and 500 percent. The results are shown in figures 12 through 14. Once again, the estimates do not converge to the predicted values indicating sensitivity to unmodelled dynamics. However, the existence of a degradation is apparent and the estimates scale with the amount of degradation introduced.

The effects of oxygen side degradations on the estimate of B16 is also of interest from a separability standpoint. Degradations of parameters unrelated to LPFT efficiency should be transparent to the estimator. A 5% degradation in the high pressure oxidized turbopump (HPOT) efficiency has been introduced in the Matrix_x simulation with results shown in figures 15 and 16. In this case, the open loop results show that this is interpreted as a LPFT efficiency degradation. This is expected since the HPOT significantly affects the LPFT and this relationship is not included in the reduced order filter model. The closed loop results are unaffected by the HPOT efficiency degradation which is a good example of the controller masking information used by the filter.

Conclusions

This paper gives a brief overview of the extended Kalman filter and how it can be modified to act as a parameter estimator for Space Shuttle Main Engine (SSME) turbomachinery. Off-line results show the shortcomings of a reduced order filter for estimating the high pressure fuel turbine efficiency. Satisfactory estimates have been achieved for the low pressure fuel turbopump. Preliminary results using a full order model in the filter indicate that this modification can overcome the problems for the high pressure turbopump at the expense of a more complex filter implementation.

On-line implementation of the extended Kalman filter (EKF) for a complex engine like the SSME presents a number of technical challenges. Here, we have suggested several modifications to improve execution speed without impacting filter performance. However, real-time execution for the SSME would be difficult without a significant increase in computing power and more efficient programming methods.

On-line results also show that the parameter estimates are satisfactory when a closed loop control is present and appear to be insensitive to controller structure. Thus, the EKF can be used in an on-line environment to provide turbopump efficiency estimates for use in a health monitoring scheme for the SSME. Finally, on-line results have demonstrated the filter's sensitivity to unmodelled dynamics. These results, in addition to the off-line results, indicate that the dynamics included in the filter model must be chosen carefully to accommodate the type of degradations that might be expected.

Acknowledgments

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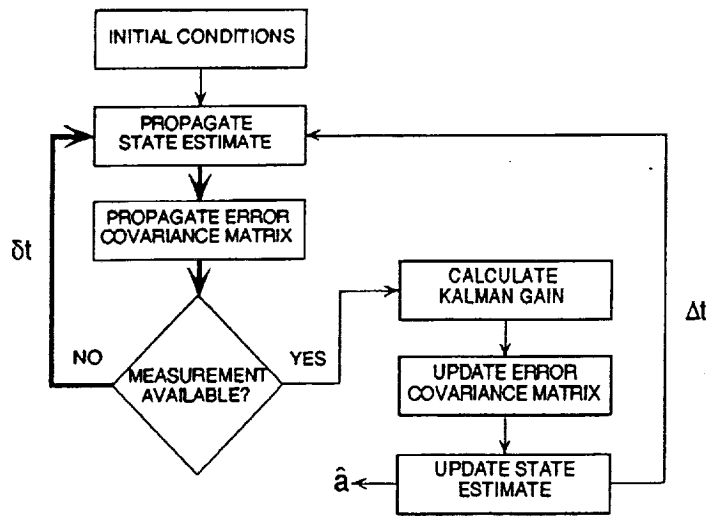


Figure 1. Extended Kalman Filter Algorithm

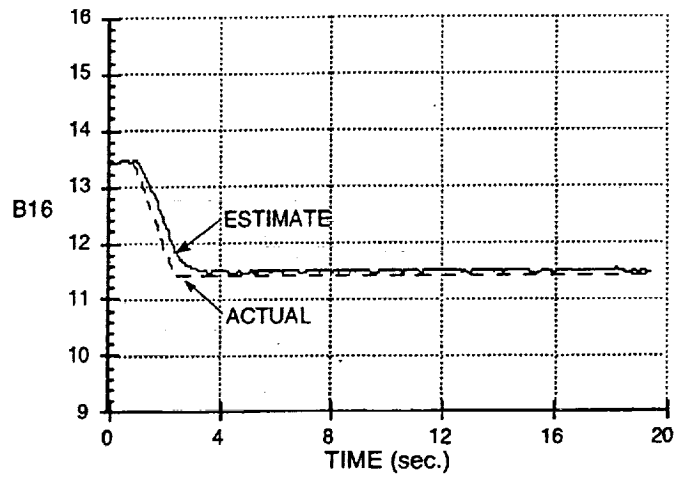


Figure 2. B16 - Off line Simulation w/ B16 Degradation

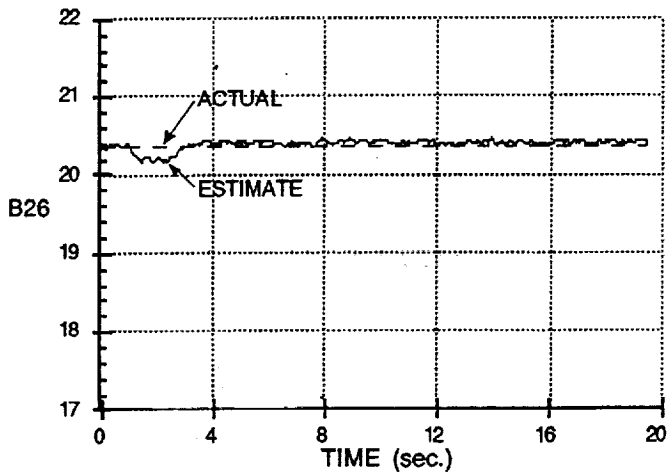


Figure 3. B26 - Off line Simulation w/ B16 Degradation

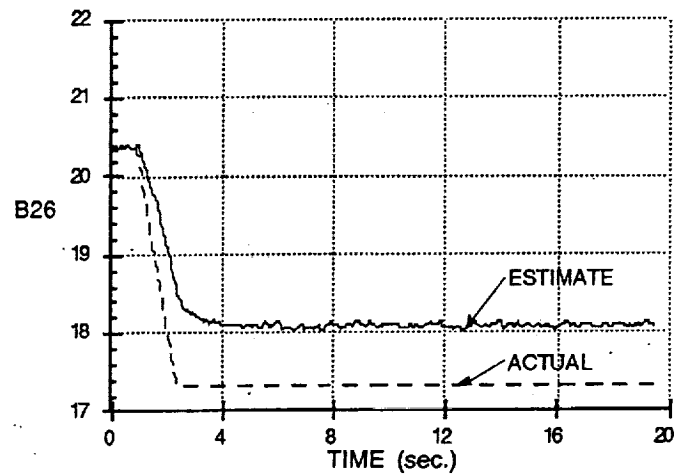


Figure 4. B26 - Off line Simulation w/ B26 Degradation

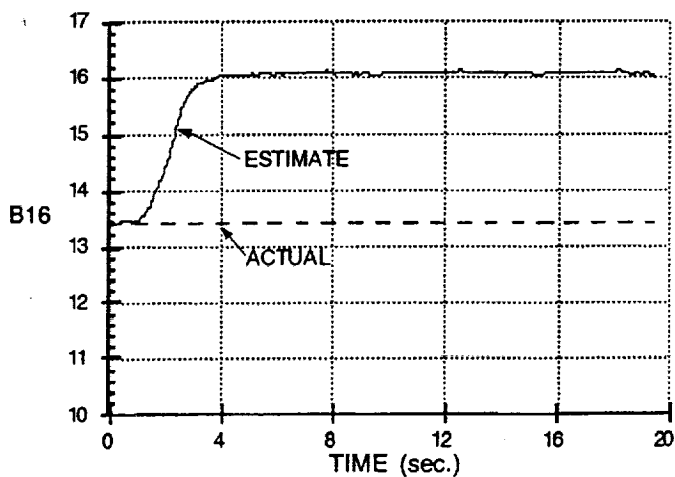


Figure 5. B16 - Off line Simulation w/ B26 Degradation

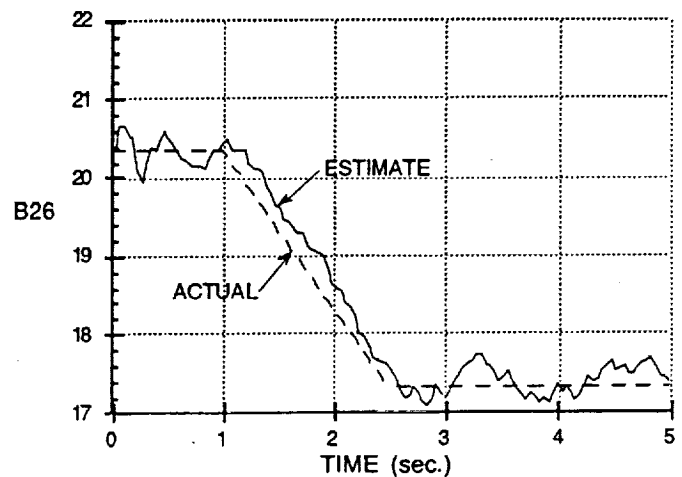


Figure 6. Full Order, Off line w/ B26 Degradation

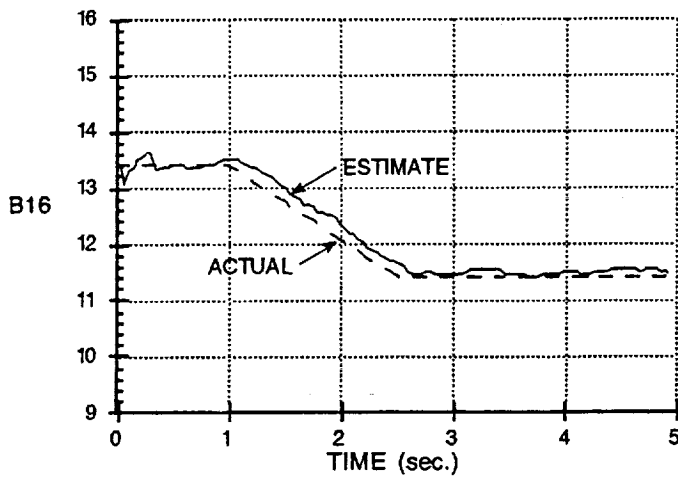


Figure 7. Full Order, Off line w/ B16 Degradation

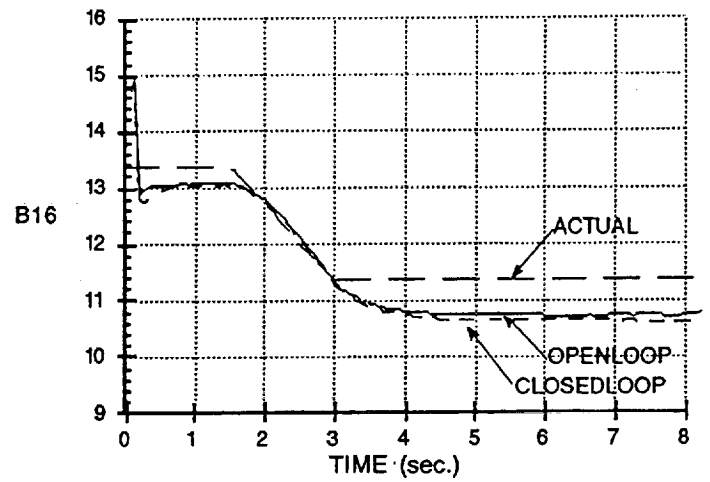


Figure 8. B16 - AD100 Simulation w/ B16 Degradation

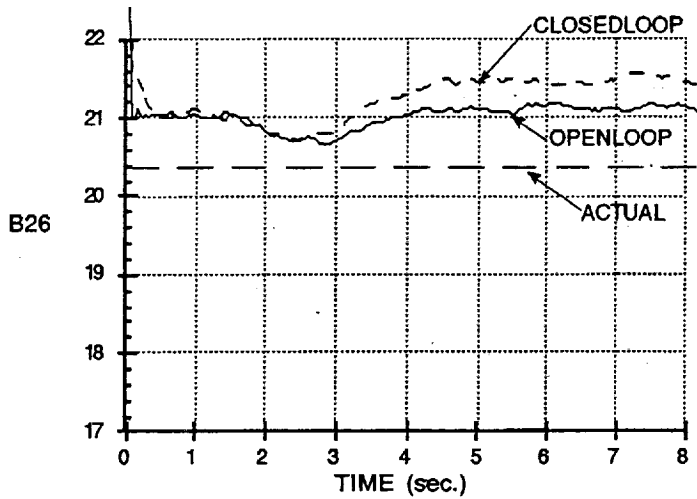


Figure 9. B26 - AD100 Simulation w/ B16 Degradation

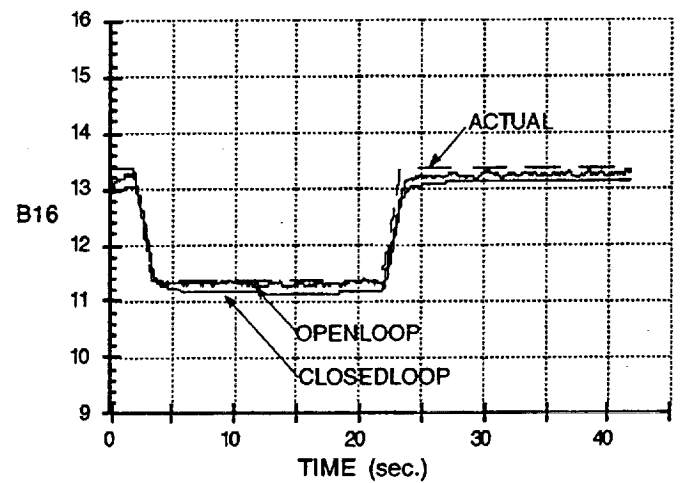


Figure 10. B16 - MATRIXx Sim. w/ B16 Degradation

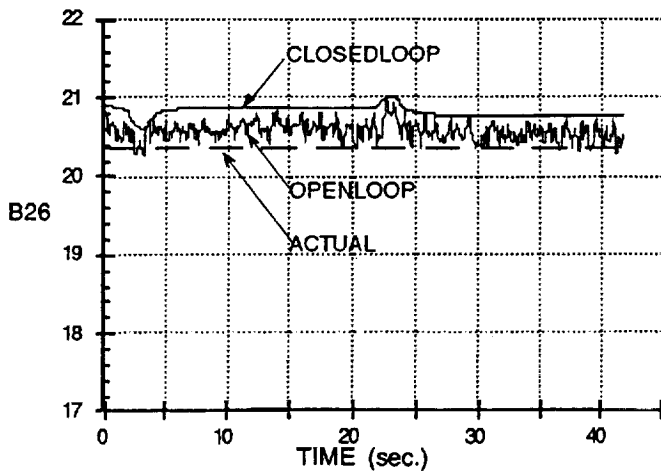


Figure 11. B26 - MATRIXx Sim. w/ B16 Degradation

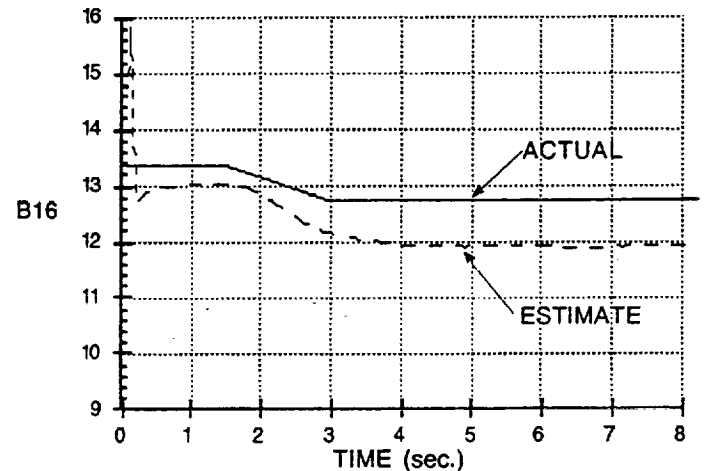


Figure 12. 250% Increase in LPFT Shaft Seal Clearance on AD100 Simulation

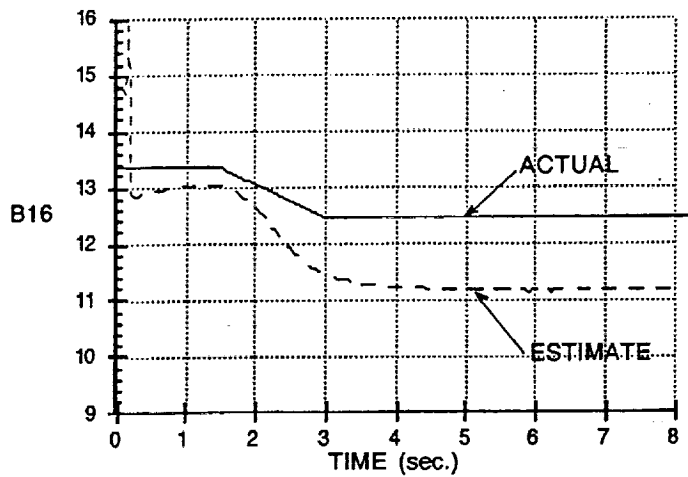


Figure 13. 500% Increase in LPFT Shaft Seal Clearance on AD100 Simulation

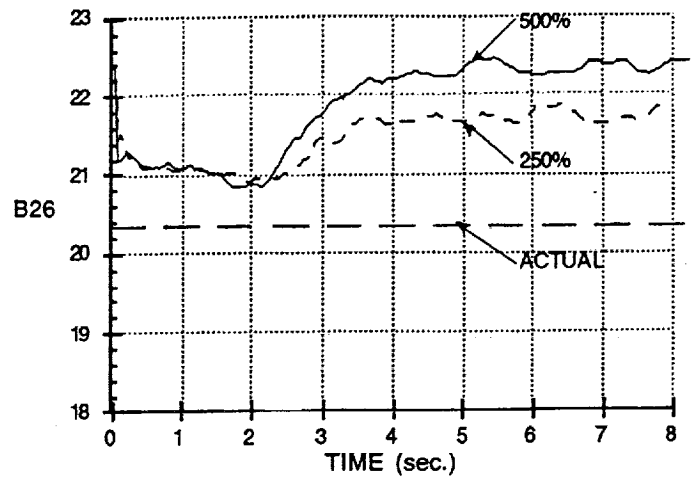


Figure 14. Increase in LPFT Shaft Seal Clearance on AD100 Simulation

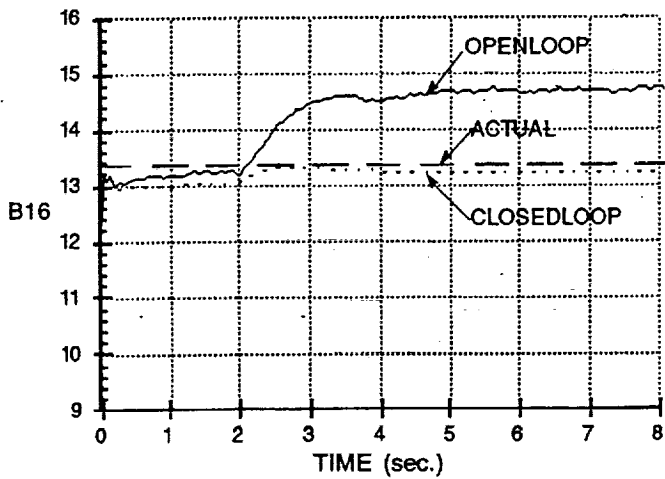


Figure 15. B16 - 5% Decrease in HPOT Efficiency on AD100 Simulation

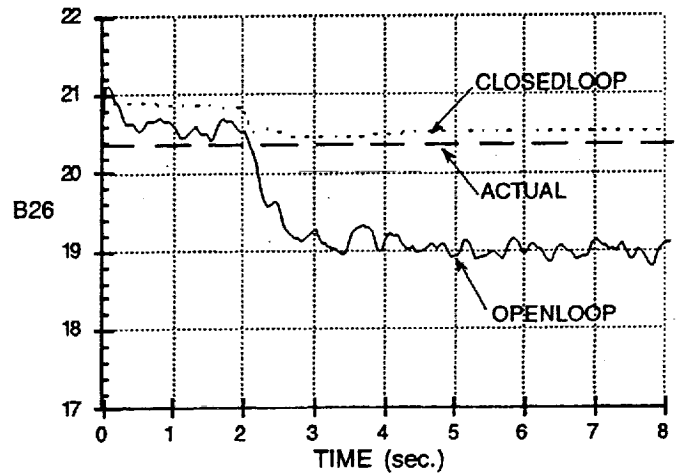


Figure 16. B26 - 5% Decrease in HPOT Efficiency on AD100 Simulation

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